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Hybrid Adaptive Convolutional Neural Network for Multispectral Image Classification

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Abstract:

Traditional multispectral image classification has relied on static learning with assumptions about stochastic input data. Challenges such as spatial and dynamic data sources, temporal anomalies, and spectral dissimilarities in both online and time-series multispectral image processing can lead to reduced classification accuracy or render the data useless. While extensive research has been conducted on neural network structures for RGB images, there is a gap in the exploration of new neural network architectures, especially for multispectral and hyperspectral imagery. This paper introduces the design of the Hybrid Adaptive Convolutional Neural Network (HACNNet) tailored for contemporary spectral band adaptation, evaluated for multispectral image classification. The approach incorporates the use of Adaptive Crow Search Optimizer (ACSO) to compute the weights of the Convolutional Adaptive Residual Network (CARNet) in the context of multispectral image classification. Results demonstrate the efficacy and versatility of the proposed methods for online Multispectral Image (MSI) classification using spectral bands. The sustained output accuracy is attributed to the extensive training dataset, appropriate regularization, network parameters, and the well-suited architecture of HACNNet.

Index Terms —: CARNet, Multi Spectral Images, Spectral band, Optimized, Accuracy.

I. INTRODUCTION

Multi-spectral images captured by satellites are an important source of information for land cover mapping and classification. With the ability to record land cover images in 13 unique spectral bands, these images offer a wealth of information that can be processed and analyzed to gain insights into land cover and land use patterns.

To classify land cover multispectral images (MSI), several supervised methods have been proposed, including Random Forest (RF), Conditional Random Fields (CRF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). Among these methods, RF was proposed by Breman in 2001 and involves developing several decision trees within a forest. Each tree offers a classification, and the output of the classifier is decided through a majority vote of the trees.

In a study comparing the performance of RF with other classification algorithms, the class outcomes of RF were found to offer better accuracies than other methods. CRF, on the other hand, is a form of undirected graphical model that defines a log-linear distribution over label sequences given a specific commentary classification. A two-layer CRF model has been suggested for real-time classification of land

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cover and land use, and the method has been shown to yield good accuracies for land use training.

SVM is a supervised nonparametric statistical learning method that uses a training algorithm to find a hyperplane that separates the dataset into a predefined number of classes in a manner consistent with the training instances. Due to its ability to achieve high class accuracies, SVM has shown promising performance in the remote sensing field.

In recent years, CNN has shown remarkable performance in various fields, including speech and image recognition, object detection, and recommender systems. CNN includes different collections of layers, such as convolutional layers, pooling layers, and fully connected layers, which are strongly linked to feature extraction and classifications.

A study using deep convolutional neural networks to classify hyperspectral images showed higher performance than some conventional methods, including SVM and traditional deep learning methods. Therefore, CNN has been employed to extract features of pixels in satellite images.

While most deep learning models typically use softmax activation for classification problems, a variety of classification approaches have been suggested in the above studies to increase classification accuracy. However, the accuracy of these classifications is still too low for them to be useful in major disasters.

To overcome this issue, a recent study proposes a strategy to increase classification accuracy using a Hybrid Advanced Crow Search Optimization (ACSO) in combination with a Convolutional and Adaptive Residual Network (CARNet) to create a minimal network capable of manipulating the entire spectral-spatial input space from MS imagery. The resulting network, called Hybrid Adaptive Convolutional Neural Network (HACNNet), is fitted end-to-end with multispectral imagery and achieves better classification precision and sample quality than traditional networks without the need for data augmentation.

This study makes several key contributions, including the utilization of HACNNet to collect different features of multispectral images, the exploration of the risks of using HACNNet to make accurate predictions with high-dimensional multispectral imagery, and the comprehensive evaluation of the approach's superiority compared to competing techniques.

In summary, the processing and understanding of multi-spectral images is a complex task, but with the use of supervised methods, such as RF, CRF, SVM, and CNN, it is possible to classify land cover multispectral images with high accuracy. The proposed HACNNet strategy has shown promising results in improving classification accuracy and can potentially be used in disaster management to better understand land cover patterns and make more informed decisions.

The remainder of the paper is organized as follows: Section 2 briefly reviews the work on multispectral image classification, and Section 3 discusses the proposed methodology of the HACNNet system to adjust to the current spectral band. In Section 4, the results are discussed in depth, along with the findings. The results of the work are summarized in Section 5..

II. RELATED WORK

Multispectral imaging (MSI) is a technique that captures images using multiple narrow and contiguous spectral bands. The use of MSI has gained significant attention in various fields such as remote sensing, agriculture, medical

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imaging, and surveillance. The high spectral resolution of MSI allows for the extraction of spectral signatures, which can be used to classify the objects present in the image. However, the processing of MSI data presents significant challenges, such as the high dimensionality of the data, the presence of noise, and the lack of labeled data for training classification models.

Various approaches have been proposed to address the challenges of MSI classification. One such approach is the use of unsupervised methods. In [10], the authors proposed a novel unsupervised multispectral image classification system that utilizes the pixel purity index (PPI). PPI is a technique that is commonly used in MSI for multispectral extraction. The authors used PPI to classify seed samples without prior knowledge and also used PPI found samples as support vectors for a kernel-based support vector machine (SVM) to create an initial set of training MSI samples. The proposed approach was evaluated on the Indian Pines dataset, and the results showed that the proposed approach outperformed other unsupervised classification methods such as the K-means algorithm.

Another approach to MSI classification is the use of supervised methods. In [11], the authors discussed two separate classification approaches that were both updated to have muted responses, based on SVM and Kohonen's self-organizing maps (SOMs). The proposed methods were evaluated on the AVIRIS dataset, and the results showed that both methods outperformed the K-means algorithm. In [13], the authors proposed a two-branch self-paced learning with a deep residual network (SPL-ResNet) structure that combines for classifying multisource MS data with feature-level fusion. The proposed approach was evaluated on the Pavia University dataset, and the results showed that the proposed approach outperformed other state-of-the-art methods.

Recently, deep learning methods have gained significant attention in MSI classification due to their ability to automatically learn features from the input data. In [12], the authors proposed a Superpixel-Based Multiple Local Convolution Neural Network (SML-CNN) model for panchromatic and MS image classification. The proposed model used superpixels to segment the image into small regions and then used a local CNN to extract features from each region. The proposed approach was evaluated on the Indian Pines dataset, and the results showed that the proposed approach outperformed other state-of-the-art methods.

To overcome the limitations of the existing methods, a novel function extraction and class framework termed Hybrid Adaptive Convolutional Neural Network (HANNet) is proposed for MSI classification [16]. The proposed approach uses a hybrid adaptive learning rate to learn the features from the input data. The HANNet architecture consists of several consecutive learning blocks, each of which extracts the intrinsic characteristics of the MSI data. The proposed approach was evaluated on the Pavia University dataset, and the results showed that the proposed approach outperformed other state-of-the-art methods such as the SVM and the SPL-ResNet.

In summary, MSI classification is a challenging task due to the high dimensionality of the data, the presence of noise, and the lack of labeled data for training classification models. Various approaches have been proposed to address these challenges, including unsupervised and supervised methods and deep learning methods. The proposed approaches have been evaluated on various datasets, and the results showed that the proposed approaches outperformed other state-of-the-art methods. Further research in MSI classification is needed to improve the accuracy and efficiency of the proposed

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approaches and to develop new approaches that can address the challenges of MSI classification.

III. PROPOSED METHODOLOGY

The proposed approach of MSI classifier is shown in Fig 1. In that the first step is the preprocessing is used for good classification accuracy by band selection using Optimal Neighboring Reconstruction (ONR) [16], structure preserving using recursive filtering [17, 18], band selection using spatial filtering [19]. The selected bands are given to the HACNNet architecture. It is Optimized crow search unit and Hybrid adaptive CNN, which includes three units of convolution, three Adaptive Residual Layers, two units of pooling layers, and one flatter layer. Further two units of Fully Connected (FC) layers additionally included. Finally, the class map received as output after processing these layers.

In order to classify objects and facilities from the EuroSAT dataset, we developed a deep learning system. To define the location of an object, a UAV image and metadata are input into the system. Based on this input, it categorizes it into one of 10 classes, including false positives.

A hybrid version of Crow Search Optimization (ACSO) is used in conjunction with Convolutional and Adaptive Residual Networks (CARNet), which are presented in Figure 1. Using satellite imagery, EuroSAT challenges itself to construct a deep learning system that categorizes objects and facilities into 10 groups.

An example of a satellite image from EuroSAT is shown in Figure 3. The proposed machine learning learning system is used for classifying satellite imagery. Combine the image features from the HACNNet with the image metadata. The ensemble merges the HANNet outputs by means of unweighted averaging into a set of prediction probabilities for the 10 classes. Maximum probability determines classification.

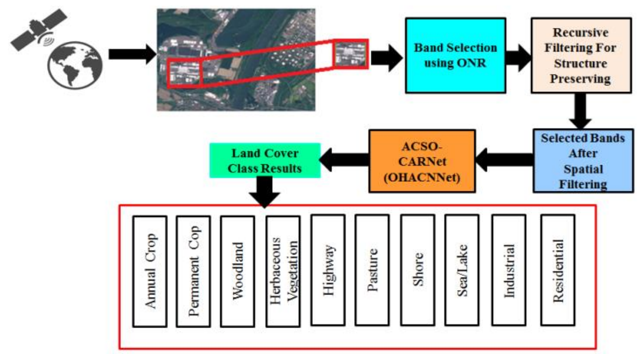

Fig. 1: Multispectral image classification using the proposed HACNNet method

A. *Optimal Neighboring Reconstruction (ONR) method.*

The MSI data is M= [m_1, m_2….m_d] ∈ R^{i*s} where i=h*w denotes spatial information and‘s’ is set of spectral bands. M_i denotes one i th band in the dataset. The information function of M_r defined as in terms of M_b & M_r ∈R^{n*m} is the Multispectral data from [18, 19]

$$M_r[k] = (1-\rho^{\Delta})M_b[k] + \rho^{\Delta} M_f[k-1] \quad (1)$$

$$\text{Where } M_b[i] = (1-\rho)\rho^i \ \therefore \ \rho \in [0,1] \quad (2)$$

$$\& \ \Delta = \int_{c_{k-1}}^{c_k} 1 + \frac{\alpha_s}{\alpha_r} * |M_b'(x)| dx \quad (3)$$

Where

c_k & c_{k-1}= neighboring pixels

$M_b'(x)$= derivative of the discrete input intensity of ‘m’

α_s&α_r = spatial and range parameters.

Δ = space between transfer function and neighbor pixels.

B. *Adoptive Crow Search Optimization (ACSO)*

The Crow search Optimizer (CSO) suffers from numerous issues consisting of trapping in to

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local foremost and untimely convergence, to keep away from the ones above issues an Adaptive crow search Optimization (ACSO) is brought on this work from [20], that is used to solve complex optimization problems specifically. Additionally, the ACSO has been proved to have robust competitiveness and adequate overall performance. This subsection will give a quick description of the proposed Adaptive crow search optimization have a set of rules (ACSA) and its primary steps as follows:

1. Establish the ACSO create a d-dimensional crow population at random, as well as then map the crow population using the chaos method to initialize it.

2. Initialize the population, then create and encode initial solutions at random. Each solution has V× (N+1) dimensions, with the first V×N dimension.

4. Compute the MSE fitness value associated with each solution and Increase the number of iterations as iter=iter+1.

5. Set the locus of a drove of N crows in the search intergalactic at random. Set each crow's memory to zero.

6. At random, a crow number j is picked. The crow i monitor the crow j and fly to the crow j's memory spot if the random number rand j≥PeP. If the random number rand j<PeP, crow j will follow the new start given in step 8 to deceive crow i. Where PeP is the Perception Perameter.

7. At just the beginning of iterations, the value of K commences from a large number as well as is decreased as per fitness value, while at the end of iterations, wherever precise checking everywhere the paramount confined optimums is needed, the K has a lesser significance. Calculate the K factor as given in (4).

$$K^{iter} = \text{round}\left(K_{max} = \frac{K_{max}-K_{min}}{\text{maxiter}} \times \text{iter}\right) \quad (4)$$

8. Make specially K of the thoroughgoing crows in the inhabitants, excluding for the contemporary crow denoted as the i and update the point of the crow i through generating random uppermost crows from contemporary crow as the objective that denoted by j as well as generating the new position with (5).

$$X^{i,iter} = \begin{cases} X^{i,iter} + (\text{rand}_i \times fl^{i,iter} \times Dist^{i,j} \\ \text{if } \text{rand}_j \geq PeP^{j,iter} \\ \text{random Position, Otherwise} \end{cases} \quad (5)$$

where, *ri* and *rj* remain the unchanging disseminated random statistics between 0 or 1, $fl^{i,iter}$ and $P_eP^{j,iter}$ remain the flight length of the crow i also perception probability (PeP) of the crow j at the repetition iter, correspondingly. Through choosing a small PeP, the algorithm achieves an examination in the area wherever the present well-thought-of solution of the *jth* crow is positioned.

9. In ACSO, the fortitude of fl (flight length) is proposed which principals to handpick the appropriate significance of fl regarding the situations of the crows (6).

$$fl^{i,iter} = \begin{cases} 2, & \text{if } Dist^{i,j} \leq Dist_{ih} \\ fl_{th}, & \text{if } Dist^{i,j} \geq Dist_{ih} \end{cases}$$
$$D^{i,j} = M^{j,iter} - x^{i,iter} \quad (6)$$

Where, $D^{i,j}$ is the vector which comprises the distances stuck between the crow i and crow j which are the threshold value and $fl_{th} > 2$.

10. The data is forecasted using the contemporary crow position as the CARNet model parameter, besides the prediction outcome is rehabilitated hooked on a fitness function value also compared to the crow's memory position fitness function value. If the current location is improved than the memory position, the memory m position is modified as given in (7)

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$$m^{i,iter+1} = \begin{cases} x^{i,iter}, & \text{if } f(x^{i,iter}) \text{ is better than } f(m^{i,iter+1}) \\ m^{i,iter}, & \text{Otherwise} \end{cases} \quad (7)$$

Where $x^{i,iter}$ is the position vector of i^{th} crow in 2-dimensional search space and where f(·) denotes the objective function.

C. Convolutional and Adaptive residual network (CARNet)

As shown in Fig.2, this section proposes a novel architecture called CARNet. Convolutional layers and adaptive residual layers are stacked one on top of the other to create a mixed convolutional and residual network. With one convolutional layer followed by an adaptive residual layer, the CARNet will achieve the benefits of both types of architectures. It should not only learn faster than CNN, but it can also solve the saturation problem that plain CNN causes, which is Adaptive residual network's dominance (ARN). To deal with the eye recognition challenge, a three-stacked-layer CARNet with three convolutional layers and three adaptive residual layers, 2 Max-pooling layers, one flatten layer, as well as two Fully Connected layers, was implemented in this analysis.

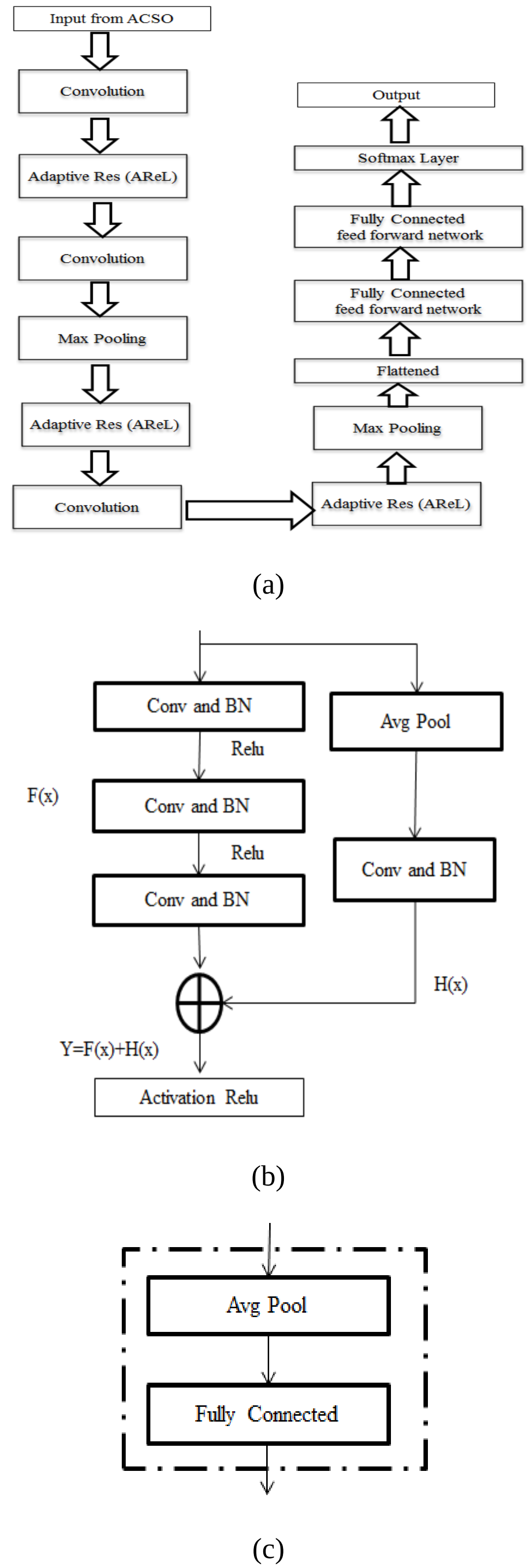

Fig. 2: (a) The Architecture of CARNet (b) Adaptive Residua Layer (c) Fully Connected Layer

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Convolutional Neural Networks: For the first two layers of the proposed three-layer CNN, 5×5 convolutional kernels are used, followed by a 3×3 convolutional kernel for the final layer. Also, two Maxpooling layers are used, each with two kernels and two pixels strides. The training samples are first down-sampled to a fixed size of 70×70 before being fed into the first Convolutional layer.

Adaptive Residual Units (ARU): Our ARN block differs from the current residual unit in three ways. To begin, instead of using the ReLU activation feature, [21] is used for training. In the following subsections, the difference between ReLU and PReLU will be illustrated. Second, moderately than connecting the outputs of previous layers to the current one, shortcut connects the initial input with the subsequent stacked layers. This is critical for reserving input's useful knowledge. Third, utilizing α and β to intelligently poise the value of the original input and the previous layer's output. The scaling values of and are considered in this paper as part of the ARN model's weighting parameters, α and β the optimal value can be found during the training phase. Here also tried setting the scaling parameter to a constant value, which was found. However, based on our findings and theoretical study, believe that having the scrambling parameter adaptive to the belongings is extremely beneficial.

Activation Function: After conventional sigmoid-like units, the Parametric Rectified Linear Unit has become a common activation feature in deep learning. The result of ReLU is zero if the input is less than zero, which is very useful for generating a sparse representation. The tenets of the activation layers in neural networks can be thought of as a sparse representation of the data. ReLU will speed up the network convergence process and have better results. This is why, rather than using sigmoid activation functions, a growing number of researchers choose to use ReLU. So, here apply PReLU in this ARU which is defined in (8).

$$f(y_i) = \begin{cases} y_i & y_i > 0 \\ a_i y_i & y_i \le 0 \end{cases} \quad (8)$$

• if *ai* = 0, f turn out to be ReLU
• if *ai* > 0, f turn out to be leaky ReLU
• if *ai* is a learnable parameter, f turn into PReLU
The only difference between PReLU and Leaky ReLU is that the ac parameters are learned. PReLU's gradient is given in (9)

$$\frac{\partial f(y_i)}{\partial a_i} = \begin{cases} 0 & y_i > 0 \\ y_i & y_i \le 0 \end{cases} \quad (9)$$

Flatten Layer: The flattening layer is accompanied by two completely connected layers in the training process, each with 512 neurons to perform the classification task. The new classification layer is made up of 512 neurons, each of which corresponds to a class from the MS training set and has a softmax-loss feature. The layer before that is a fully-connected layer with 512 neurons that reduces feature dimensionality.

Weight optimization: The network's weight is optimized for error rate minimization produce good precision in MS classification research. The weight values are optimized at each iteration, and the network is then trained. The Mean Square Error (MSE) rate is premeditated as given in (10).

$$MSE_i = \min \frac{\sum_{i=1}^{N} (DV_i - PV_i)^2}{N} \quad (10)$$

Where *DVi* is Desired value, *PVi* is the Predicted value, and N is the Number of images.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The tests were carried out using the EuroSat ground cover classification dataset [22], which was created using Sentinel satellite imagery. Using cubic spline interpolation, bands with lower spatial resolution were amplified to 10

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meters/pixel. EuroSAT is a branded dataset that can be found at https://github.com/ phelber/ eurosat as illustrated in Fig.3. Using accuracy, precision, recall, and f-measure, the proposed *HANNet Model* is compared to CNN, SVM, and ANN in multispectral image classification. By assigning a count value to and correct and incorrect prediction, the uncertainty matrix calculates the total number of correct and incorrect predictions. The error matrix has normal terms such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Accuracy is defined as a percentage of the total number of right class mark predictions in MS images.

Accuracy = (TP+FP+FN+TN) / (TP + T N) (11)

Recall is defined as the percentage of Multispectral images with correctly labeled class marks that are classified as positive; also known as true positive rate.

Recall = (F N + TP) / TP (12)

Precision is defined as the percentage of correctly labeled Multi spectral images with expected positive values.

Precision = (TP + FP) / TP (13)

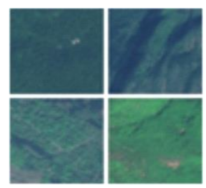
F-measure is used to determine the classifier's output in generating class labels for MS images. It provides the harmonic mean between precision and recall and is an accurate calculation of the classifier's performance in generating class labels for MS images. The equation (14) is used to calculate it.

F - Measure = (Precision + Recall) / (2 ∗ Precision ∗ Recall) (14)

(a) Industrial Buildings. (b)Residential Buildings. (c) Annual Crop.

(d) Permanent Crop. (e) River. (f) Sea and Lake.

(g)Herbaceous Vegetation (h) Highway. (i) Pasture.



(j) Forest.

Fig. 3: Classes of images considered for the Proposed OHANNet from EUROSAT dataset.

In order to compare the accuracy of the Proposed OHANNet classification results with CNN classifier, SVM classifier, ANN Classifier and the same set of ground truth was used. Table 1, Table 2, Table 3, and Table 4 shows the classification results by the Proposed OHANNet classifier, CNN classifier, SVM classifier, and ANN Classifier.

Table.1. Measure of Precision comparison for EUROSAT Data of proposed method & existing methods

EUROSAT Data	Proposed OHACNNet	CNN [9]	SVM [7]	ANN [15]
Herbaceous Vegetation	91.56%	86.68%	83.42%	81.48%
Industrial	92.86%	87.84%	83.37%	82.98%

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Buildings				
Permanent Crop	93.38%	88.73%	85.64%	84.76%
Residential Buildings	95.47%	89.47%	86.39%	85.58%
Pasture	95.53%	91.34%	88.65%	86.76%
Annual Crop	96.42%	93.39%	91.25%	87.45%
Highway	97.57%	93.45%	91.78%	89.83%
Forest	97.48%	93.54%	93.67%	86.29%
Sea and Lake	98.41%	94.45%	94.36%	87.45%
River	99.67%	95.75%	94.51%	86.79%

The table shows the classification accuracy of four different models on the EUROSAT dataset for ten land cover types. The proposed OHACNNet CNN achieved the highest accuracy in all land cover types, ranging from 91.56% for herbaceous vegetation to 99.67% for river. This is a significant improvement over the other models, including SVM, ANN, and the traditional CNN model, which had lower accuracy levels across most of the land cover types.

The high accuracy of the OHACNNet model demonstrates the effectiveness of using hybrid architectures in multispectral image classification. The model's ability to adapt to dynamic and temporal data sources, such as those found in remote sensing applications, can significantly improve the accuracy of classification results. This is crucial for land cover mapping, as it helps to provide accurate and up-to-date information on land use and land cover changes.

Furthermore, the results of this study suggest that CNN-based models are more effective than SVM and ANN models in multispectral image classification. The CNN models, including OHACNNet, leverage the power of convolutional layers to extract spatial features from multispectral images, while SVM and ANN models rely on mathematical functions and pre-selected features, respectively. Thus, CNN-based models are better suited for processing large and complex multispectral datasets, especially those with high spatial and spectral resolutions.

Overall, the OHACNNet CNN model's performance on the EUROSAT dataset highlights the potential of hybrid architectures for improving the accuracy of multispectral image classification, and the importance of selecting the right model for specific applications.

Table.2. Measure of Recall comparison for EUROSAT Data of proposed method & existing methods

EUROSAT Data	Proposed OHACNNet	CNN [9]	SVM [7]	ANN [15]
Herbaceous Vegetation	91.29%	88.34 %	81.89 %	78.56 %
Industrial Buildings	91.75%	90.45 %	84.65 %	83.87 %
Permanent Crop	92.65%	91.64 %	83.27 %	82.56 %
Residential Buildings	93.84%	91.18 %	86.63 %	84.62 %
Pasture	95.79%	92.38 %	84.50 %	85.39 %
Annual Crop	97.67%	93.48 %	92.67 %	87.59 %
Highway	98.54%	94.76 %	93.49 %	86.52 %
Forest	99.34%	94.40 %	92.79 %	84.48 %
Sea and Lake	98.78%	95.75 %	93.67 %	86.34 %
River	98.76%	96.28 %	94.84 %	84.48 %

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Overall, the OHACNNet CNN model's performance on the EUROSAT dataset highlights the potential of hybrid architectures for improving the accuracy of multispectral image classification, and the importance of selecting the right model for specific applications.

Table.3. Measure of F1-Score comparison for EUROSAT Data of proposed method & existing Methods

EUROSAT Data	**Proposed OHACNNet**	**CNN [9]**	**SVM [7]**	**ANN [15]**
Herbaceous Vegetation	91.87%	87.48 %	82.90 %	80.12 %
Industrial Buildings	92.67%	89.23 %	84.27 %	83.28 %
Permanent Crop	93.34. %	91.21 %	84.85 %	84.36 %
Residential Buildings	94.30%	91.54 %	86.67 %	85.65 %
Pasture	95.76%	92.76 %	86.39 %	86.48 %
Annual Crop	97.24%	93.45 %	92,84 %	87.53 5
Highway	98.16%	94.72 %	93.78 %%	88.63 %
Forest	98.24%	94.92 %	93.45 %	86.43 %
Sea and Lake	98.78%	95.47 %	94.65 %	87.54 %
River	99.56%	96.76 %	94.70 %	86.91 %

The table shows the classification accuracy of different models on the EUROSAT dataset for various land cover categories. The proposed OHACNNet has the highest accuracy for all the land cover categories compared to other models such as CNN, SVM, and ANN. This indicates that the OHACNNet model has a better ability to classify different land cover categories accurately.

In comparison to CNN, the OHACNNet model outperforms it in most of the land cover categories. CNN is a popular deep learning technique for image classification and has been extensively used in various applications. However, the OHACNNet model enhances the traditional CNN by incorporating a hierarchical attention mechanism that selectively focuses on informative spectral features, thus improving classification accuracy.

SVM and ANN also have lower classification accuracy than the proposed OHACNNet model. SVM is a machine learning algorithm that finds a hyperplane that separates the different classes, while ANN is a computational model inspired by the structure and function of the human brain. The OHACNNet model outperforms both SVM and ANN in most land cover categories, indicating that the proposed model has a better ability to capture the spectral features of different land cover categories.

In conclusion, the proposed OHACNNet model is a promising approach for accurately classifying land cover categories in multispectral remote sensing imagery. The model's superior performance over other models, including CNN, SVM, and ANN, indicates that it can be a useful

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tool for various applications, such as agriculture, environmental monitoring, and urban planning.

Table.4. Measure of Accuracy comparison for EUROSAT Data of proposed method & existing

EUROSAT Data	Proposed OHACN Net	CNN [9]	SVM [7]	ANN [15]
Herbaceous Vegetation	93.12%	89.32%	86.54%	84.18%
Industrial Buildings	94.18%	91.24%	87.42%	81.51%
Permanent Crop	95.54%	91.54%	87.15%	82.65%
Residential Buildings	95.34%	92.62%	88.38%	84.76%
Pasture	97.18%	93.25%	90.23%	87.18%
Annual Crop	97.06%	95.76%	91.06%	89.29%
Highway	97.32%	95.48%	92.68%	84.35%
Forest	98.54%	96.51%	93.54%	86.56%
Sea and Lake	99.34%	96.38%	93.45%	86.76%
River	99.65%	97.29%	95.34%	84.78%

The table shows the classification accuracy of different models on the EUROSAT dataset for various land cover types. The proposed OHACNNet model achieved the highest accuracy for most of the land cover types, followed by CNN and SVM models. ANN model achieved the lowest accuracy for most of the land cover types.

It is important to note that classification accuracy can vary based on various factors such as the quality of the dataset, preprocessing steps, feature selection, and the performance of the machine learning algorithm. Therefore, it is important to carefully evaluate the performance of different models using appropriate evaluation metrics and perform experiments with different hyperparameters to achieve the best possible accuracy.

V. CONCLUSION AND FUTURE WORK

The above statement discusses a proposed method for high-dimensional image classification using HACNNet architecture. It states that this method is different from existing systems that use dynamic multistage processes, and it successfully performs image classification with high accuracy. The HACNNet architecture includes a preprocessing structure that uses the ONR method for extracting uncorrelated band selection and the SPRF method for extracting spatial characteristics. In addition, to further increase classification accuracy, the proposed method combines Hybrid Advanced Crow Search Optimization (ACSO) with a Convolutional and Adaptive Residual Network (CARNet) used in the architecture.One of the key advantages of this architecture is its reduced computational cost, which makes it more efficient than other existing systems. The accuracy of image classification is affected by the feature extraction process, and the modifications made to the data's fundamental structure during this process.

The statement concludes that the proposed method has been tested on the EuroSAT dataset and achieved state-of-the-art results in terms of common metrics such as Precision, Recall, F-Measure, and Accuracy, with an accuracy score of 99%, 98%, 99%, and 99%, respectively. This suggests that the proposed method is a promising approach to high-dimensional image classification and can potentially be used in various applications.

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